## Supplemental information

# Rapid tree carbon stock recovery in Amazonian managed forests

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Inventory of Supplemental Information:
Tables S1 and S2
Experimental Procedures
Acknowledgements
Supplemental References

**Due to limited space availability, we provide supplemental online information (OS), graphs and analysis at: http://tmfo.org/Data/CurrentBio.SI/TmFO.code.Amazon.html**

Table S1: Information on ACS stocks over time and recovery rates for each of the 90 plots included in this study (provided as an Excel file). Eleven (11) plots (in italic) were discarded from the analysis

Table S2: Alternative models with ΔBIC < 5.

| Model | $ACS_0$ lost (%) | $ACS_0$ | bulk density | CEC | clay | rainfall | seasonality | BIC | delta | AIC | delta | df | logLik | weight |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | 1.1064 | | | | | | | 248.9015 | 0 | 241.79 | 0 | 3.0000 | -117.8966 | 0.1443 |
| 6 | 0.9978 | | 0.2537 | | | | | 252.5302 | 3.629 | 243.05 | 1.48 | 4.0000 | -117.5262 | 0.0688 |
| 66 | 1.0443 | | | | | | 0.0032 | 252.6067 | 3.705 | 243.13 | 1.556 | 4.0000 | -117.5644 | 0.0662 |
| 4 | 1.0332 | 0.0518 | | | | | | 253.0193 | 4.118 | 243.54 | 1.969 | 4.0000 | -117.7707 | 0.0539 |
| 18 | 1.1230 | | | | -0.0014 | | | 253.1164 | 4.215 | 243.64 | 2.066 | 4.0000 | -117.8193 | 0.0513 |
| 34 | 1.1131 | | | | | 0.0000 | | 253.2668 | 4.365 | 243.79 | 2.216 | 4.0000 | -117.8945 | 0.0476 |
| 10 | 1.1038 | | | 0.0003 | | | | 253.2670 | 4.366 | 243.79 | 2.217 | 4.0000 | -117.8946 | 0.0476 |

## Supplemental Experimental Procedure

### 1. Site selection and biometric data collection

Ten (10) sites spread across the Amazon Basin and the Guiana Shield were selected based on the following criteria: (i) located in tropical forests with a total area inventoried ≥ 1 ha; (ii) mean annual rainfall ≥ 1000 mm (Fig. S1); (iii) consistent and detailed information about logging treatments (e.g. number of stems harvested and correspondent biomass removal) and logging impacts (e.g. logging damages assessment); (iv) at least one pre-logging and (v) at least two post-logging censuses. As sites were generally established by different organizations, there is no standardized protocol for data collection among sites, but all sites comply with generally agreed standards [S1]. A general description of the sites can be found in [S2]. In all plots, trees ≥ 20 cm DBH (diameter at breast height) had their girth measured at 130 cm or above buttresses/deformations, and were tagged and identified to the lowest taxonomical level.

### 2. Data quality checking and biomass computation

To avoid bias due to discrepancies in data quality (e.g. difference in botanical identification or tree species wood density information), a standardized protocol was applied to each site. At first, botanical identification was checked to match the Global Wood Density Database (GWDD) classification [S3]. Tree species present in GWDD were assigned correspondent dry wood density (WD, $gr.cm^{-3}$). When only the genus was present, genus-average WD was assigned and for unidentified species and species not present in the GWDD, plot-average WD was attributed. In the absence of tree height measurements, tree above-ground biomass (AGB) was estimated using the generic allometric model developed by Chave et al. [S4] and including WD, DBH and a synthetic climatic index (E).

Above-ground carbon density (ACS) was obtained by multiplying tree biomass by 0.47 [S5]. ACS stock of each plot was further computed as the sum of ACS of live trees DBH ≥ 20 cm divided by the plot surface and expressed in Mg C ha$^{-1}$.

### 3. Definition of logging intensity and biomass recovery

The same definition of logging intensity was applied at all sites. Due to varying interval length (1 to 4 years) between pre- and post-logging censuses and application of silvicultural treatments (i.e. poisoning, girdling, understorey clearing) at three sites (Paracou, Tapajos and la Chonta), we estimated the minimum carbon stock ($ACS_{min}$, Fig. OS2) attained at last within 4 years after logging and computed the difference with initial carbon stock ($ACS_0$). This initial ACS drop off, referred to as $ACS_{loss}$, is due to both timber harvest and mortality of damaged trees (that can affect up to 46% of remaining trees [S6]). As residual mortality peaks within the first years preceding logging [S7-8], this approach allows most of logging-induced mortality to be accounted.

We found no evidence of deviation from linearity; therefore, we estimated the annualized ACS recovery rates (Mg C ha$^{-1}$ yr$^{-1}$) per plot using linear models among all post-logging censuses spreading between $t_{min}$ and $t_{final}$ (Figure OS3).

Recovery time ($t_{rec}$ in years) refers to the estimated time needed to recover initial ACS stock, given by dividing initial ACS loss by the average recovery rate.

### 4. Relationship between recovery times and recovery rates

While ACS recovery rates are related to the capacity of a given forest to recover from a disturbance, the recovery time $t_{rec}$ accounts for both the recovery rate and the disturbance intensity (see above). The below demonstration reveals how both variables are mechanically related. By definition:

$$t_{rec} = \frac{|ACS_{loss}|}{ACS\ \widehat{recovery}\ rate}$$

From our results:

$$\log(t_{rec}) \propto \theta \times \log\left(\frac{|ACS_{loss}|}{ACS_0}\right)\ for\ \frac{|ACS_{loss}|}{ACS_0} \in [0.05, 0.5]$$

$$t_{rec} \propto \left(\frac{|ACS_{loss}|}{ACS_0}\right)^{\theta}$$

$$\frac{|ACS_{loss}|}{\widehat{recovery}\ rate} \propto \left(\frac{|ACS_{loss}|}{ACS_0}\right)^{\theta}$$

From our results, θ was found to be N (1.106, 0.022) close to 1, meaning that we are very close to

$$\widehat{recovery\ rate} \propto ACS_0$$

Mechanically, recovery rates could thus depend directly on initial ACS stocks. However, recovery rate relates to more complex mechanisms of forest productivity (i.e. growth, recruitment and mortality) and deserves a separate thorough analysis.

### 5. Explanatory variables

Several explanatory variables were calculated at each site: (1) average pre-logging ACS stock ($ACS_0$ in Mg C ha$^{-1}$); (2) Basal Area-weighted wood density (or community wood density, $WD_{BA}$ in g.cm$^{-3}$); (3) stem density (ha$^{-1}$); (4) average annual rainfall (mm yr$^{-1}$) that arose from local weather stations; (5) rainfall seasonality (annual standard deviation) were extracted at each site using WorldClim data [S9] using highest resolution (30 arc-seconds or ~1 km). Due to lack of information at all sites, soil properties were extracted from the Harmonized World Soil raster at a resolution of 30 arc-seconds [S10]. Information on top soil (0-30 cm) quality was extracted at each site: texture, drainage, available water content (range), clay, silt and sand content (%), cation-exchange capacity (CEC, cmol/kg) and bulk density (kg/dm$^3$).

To test for possible circularity between the synthetic climatic index (E) used to compute ACS and the climatic explanatory variables, all analysis were recomputed with another generic allometric model [S11], based on local WD and DBH only. All pattern and variables significance remained unchanged (data not shown).

### 6. Plot selection and weighing

To ensure that observed biomass recovery was mainly related to logging and to avoid bias due to stochastic natural mortality (e.g. the 2005 drought and fires), we selected only plots (79 out of 90) with positive recovery rates (e.g. that gain biomass/carbon over the monitored period), as a detailed checking revealed that those 11 plots suffered from wildfires and droughts. As our sample plots and sites vary in both total area and length of time monitored for, the contribution of each site was weighted by the monitoring effort (number of censuses x plot size), as recommended by [S12]. Hence, sites with longer and larger monitoring (more prone to capture and depict forest recovery) are given more weight. To avoid artificial inflation of the variance of random effects, the sum of weights was set to 1. Table S1 provides information on initial and final ACS, ACS loss, recovery rate and recovery time for each plot (N=90).

### 7. Variable selections

Our main point was to understand generic drivers that led recovery time and recovery rate among all sites. We developed a linear mixed model (LMM, package *lme4* [S13]) in which recovery time and rate were tested over the different biometric response variables defined above. To account for the site effect, we introduced a random site effect. Indeed, most sites are constituted of several contiguous plots in which silviculture treatments (e.g. logging, girdling or understorey clearing) of varying intensities were applied. Such experimental design ensures a relative homogeneity in environmental conditions and forest structure, but might also induce pseudo-replication. Pseudo-replication occurs when multiple samples from a single treatment unit are analyzed, as if they were independent replicates and embed to distinguished the effect due to treatment from other sources of variation [S14]. To avoid this bias, a “site-effect” was introduced in the LMM and pre-logging forest structures were accounted for as explanatory variables in the analysis.

The best models are found through conducting an exhaustive screening and ranking using Bayesian Information Criterion (BIC) (package *lmerTest* [S15]). Instead of picking a single “best” model, we averaged the fits of a number of “good” models (model averaging) based on Bayesian Information Criterion (BIC) weights, thereby stressing prediction over precision [S16]. Very good fits were effectively found at each site (Figure OS3). To reduce residual heteroscedasticity, recovery time along with two explanatory variables (ACS logged and number of trees harvested) was log-transformed. Table S2 shows alternative models with $\Delta\text{BIC} < 4$.

All analyses were carried out with R language and environment [S 17].

### 8. Assessing the effect of logging techniques

We ran a second analysis including logging techniques (conventional (CL) and reduced impact (RIL) logging), as a binary variable with an interaction with ACS loss. We found that logging techniques had a significant effect and improved predictions of $t_{rec}$ (BIC = 244.26 vs. 248.9, OS). However, we highly doubt the validity of this result, as conventional (CL) logging was applied at only 2 sites (Paragominas and Tabocal), representing only 7.7% of all plots used in our study. Moreover, both techniques were implemented at Paragominas only, with marked difference in post-logging dynamics [S18]. Due to its size (24.5 ha), this site has a strong leverage in our analysis, leading to conclusions that have little ecological meaning and robustness.

While an increasing number of studies reveals the benefit of RIL techniques for preserving vital environmental services [S19–21], we believe that our dataset is not robust enough to efficiently test for such an effect. Our sites were implemented over the past 30 years, while the concept of RIL techniques emerged in the 90’s.. However, we do not believe that such a simple dichotomy might reflect the differences in logging techniques, intensity and damages found among our sites. For this reason, we have adopted a broad definition of ‘ACS loss’ that account for both tree harvested and injured/killed and form a gradient of intensity *sensus largo*, at which RIL forms the lower bound. We think that this approach reflects better the diversity of logging types encountered in our dataset.

## Supplemental Author Contributions

L.D., L.M., MdO, K.R., CdS., M.T., E.V, V.W. provided summary statistics at their sites. E.R. and B.R. formatted, checked and analysed the data. E.R., B.R. and P.S. wrote the manuscript. All authors equally contributed in elaborating the protocol and proof-reading the manuscript. All authors read and approved the final manuscript.

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